International Journal of Electrical and Electronics Engineering Research (IJEEER)
ISSN(P): 2250-155X; ISSN(E): 2278-943X
Vol. 4, Issue 1, Feb 2014, 77-84

AN AUTOMATED TECHNIQUE FOR DIABETIC DAMAGE DETECTION THROUGH BLOOD VESSEL SEGMENTATION IN RETINAL IMAGES

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ABSTRACT

This paper presents a new supervised method for blood vessel detection in digital retinal images. This method uses a neural network scheme for pixel classification and computes a 7-D vector composed of gray-level and moment invariants based features for pixel representation. The method was evaluated on the publicly available **DRIVE** and **STARE** databases, widely used for this purpose, since they contain retinal images where the vascular structure, vessel endothelium and fund us features has been precisely marked by experts. Analysis of the designed technique on different kind of images that is on DRVIE database and compare to existing blood vessel segmentation techniques. Method performance on both sets of test images is better than other existing solutions in literature. The method proves accurate for blood vessel detection and its performance analyzed segmentation approaches. With this simplicity and fast implementation, make this blood vessel segmentation proposal suitable for retinal image computer analyses such as automated screening for early diabetic retinopathy detection.

KEYWORDS: Diabetic Retinopathy, Moment Invariants, Vessel Segmentation

INTRODUCTION

Diabetic retinopathy (DR) is the leading Ophthalmic pathological cause of blindness among people of working age in developed countries. The estimated prevalence of diabetes for all age groups worldwide was 2.8 % in 2000 and 4.4 % in 2030, meaning that the total number of diabetes patients is forecasted to rise from 171 million in 2000 to 366 million in 2030. The main cause of DR is abnormal blood glucose level elevation, which damages vessel endothelium, thus increasing vessel permeability. The first manifestations of DR are tiny capillary dilations known as micro aneurysms. DR progression also causes neo vascularization, hemorrhages, maculargedema and, in later stages, retinal detachment.

Although DR is not acurable disease, laser photo coagulation can prevent major vision loss if detected in early stages. However, DR patients perceive no symptoms until visual loss develops, usually in the later disease stages, when the treatment is less effective. So, to ensure the treatment is received in time, diabetic patients need annual eye-fundus examination. However, this preventive action involves a huge challenge for Health Systems due to the huge number of patients needing ophthalmologic revision, thus preventing many patients from receiving adequate treatment. Therefore, DR also becomes a great economic problem f or Administrations since, only in U. S., cost of ophthalmic chronic complications caused by diabetes exceeded 1 billion dollars in 2007.

Since vascular anomalies are one of DR manifestations, automatic assessment of eye-fund us blood vessels is necessary for automated detection of DR. As a previous step, vessel assessment demands vascular tree segmentation from the background for further processing. Knowledge on blood vessel location can be used to reduce the number offalse

positive sin micro an eurysmandhemorrhage detection. Besides these applications motivated by automated early detection of DR, vascular tree segmentation proves useful for other clinical purposes are evaluation of there tinopathy of prematurity, arteriolar narrowing, vessel tortuosity to characterize hypertensive retinopathy, vessel diameter measurement to diagnose hypertension and cardiovascular diseases, and computer- assisted laser surgery, among others. On the other hand, the vascular tree can also be useful as valuable information to locate other fundus features such as the optic disc [10] and the fovea. Moreover, it may serve as a mean for the registration of multimodal images.

In this paper, anew methodology for blood vessel detection is presented. It is based on pixel classification using a 7-D feature vector extracted from preprocessed retinal images and given as input to a neural network. Classification results (real values between 0and1) are threshold to classify each pixel into two classes: vessel and non vessel. Finally, a post processing fills pixel gaps in detected blood vessels and removes falsely detected isolated vessel pixels.

PROPOSED VESSEL SEGMENTATION METHOD

This paper proposes a blood vessel detection based on pixel classification. The necessary feature vector is computed from preprocessed retinal images in the neighborhood of the pixel under consideration. The following process stages may be identified as1) original fund us image preprocessing for gray-level homogenization and blood vessel enhancement, 2) feature extraction for pixel numerical representation, 3) application of a classifier to label the pixel as vessel or non vessel, and 4) post processing for filling pixel gaps in detected blood vessels and removing falsely detected isolated vessel pixels.

Input images are mono chrome and obtained by extracting the green band from original RGB retinal images. The green channel provides the best vessel- background contrast of the RGB-representation, while the red channel is the brightest color channel and has low contrast, and the blue one offers poor dynamic range. Thus, blood containing elements in the retinal layer (such as vessels) are best represented and reach higher contrast in the green channel

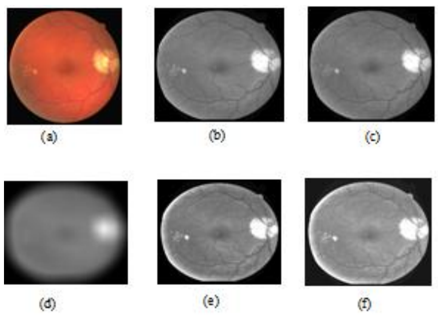

Figure 1: Illustration of the Preprocessing Process: (a) Input Image (b) Green Channel Component (c) Fundus Region after Applying Morphological Opening Operation (d) Background Image (e) Shade-Corrected Image (f) Homogenized Image

Preprocessing

Color fundus images often show important lighting variations, poor contrast and noise. In order to reduce these imperfections and generate images more suitable for extracting the pixel features demanded in the classification step, a pre- processing comprising the following steps is applied I) vessel central light reflex removal, II) background homogenization, and III) vessel enhancement.

Vessel Central Light Reflex Removal

Since retinal blood vessels have lower reflectance when compared to other retinal surfaces, they appear darker than the background. Although the typical vessel cross-sectional gray-level profile can be approximated by a Gaussian

shaped curve (inner vessel pixels are darker than the outermost ones), some blood vessels include a light streak (known as a light reflex) which runs down the central length of the blood vessel. To remove this brighter strip, the green plane of the image is filtered by applying a morphological opening using a three-pixel diameter disc, defined in asquare grid by using eight convexity, as structuring element. $I\gamma$ denotes the resultant image.

Background Image Removal

Retinal images often contain background intensity variations that is background pixel may have different intensity for same image, gray levels in background are higher than vessel pixels. With the purpose of removing these background lightening variations, a shade corrected image (Isc) is accomplished from a background estimate. After that filter by large arithmetic mean kernel convolving the resultant image with a Gaussian kernel. The difference D between $I\gamma$ and I_B is calculated for every pixel

$$D(x,y) = I\gamma(x,y) – I_B(x,y).$$

Finally, a shade- corrected image Isc is obtained by transforming whole range of possible gray-levels ([0-255]) referred to8-bitimages).The proposed shade correction algorithm is observed to reduce background intensity variations and enhance contrast in relation to the original green channel image. The histogram of I_{SC} is displaced toward the middle of the gray-scale by modifying pixel intensities according to the following gray-level global transformation function:

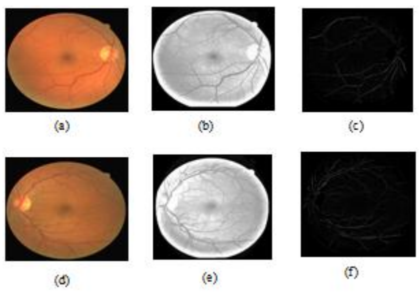

Figure 2: Two Examples of Application of the Preprocessing on Two Images with Different Illumination Conditions (a), (d) Green Channel of the Original Images (b), (e) Homogenized Images (c), (f) Vessel-Enhanced Images

Vessel Enhancement

Vessel enhancement is performed by estimating the complementary image of the homogenized image (IH) and applying the morphological Top-Hot transformation.

The darker structure remaining after the opening operation become enhanced by using Top-Hat transform

$$I_{VE} = I^c_H – \gamma(I^c_H)$$

where γ is amorphological opening operation using a disc of eight pixels in radius.

Feature Extraction

The aim of the feature extraction stage is pixel characterization by means of a feature vector, a pixel representation in terms of some quantifiable measurements which may be easily used in the classification stage to decide whether pixels belong to are al blood vessel or not.

- **Gray Level Based Features**: Features based on the differences between the gray-level in the candidate pixel and a statistical value representative of its surroundings.

- **Moment Invariants Based Features**: Features based on moment in variants for describing small image regions formed by the gray- scale values of a window centered on the rep- resented pixels.

A set of gray-level-based descriptors taking this information into account were derived from homogenized images I_H considering only a small pixel region centered on the described pixel(x,y). $S^w_{x,y}$ stands for the set of coordinate sina w×w sized square window centered on point (x,y). These descriptors can be expressed as

$$f_1(x,y) = I_H(x,y) - \min\{I_H(s,t)\}$$

RESULTS

Performance Measures

In order to quantify the algorithmic performance of the pro- posed method on a fundus image, the resulting segmentation is compared to its corresponding gold-standard image. This image is obtained by manual creation of a vessel mask in which all vessel pixels are set to one and all non vessel pixels are set to zero. Thus, automated vessel segmentation performance **c**an be assessed.

Table 1: Contingency Vessel Classification

	Vessel Present	Vessel Absent
Vessel detected	True Positive (TP)	False Positive (FP)
Vessel not detected	False Negative (FN)	True Negative (TN)

In this algorithm was evaluated in terms of sensitivity(Se), specificity(Sp), positive predictive value (Ppv), negative predictive value(Npv), and accuracy(Acc).Taking Table into account, these metrics are defined as

$$Se = \frac{TP}{TP+FN} \qquad Sp = \frac{TN}{TN+FP}$$

$$Ppv = \frac{TP}{TP+FP} \qquad Npv = \frac{TN}{TN+FN}$$

$$Acc = \frac{TP+TN}{TP+FN+TN+FP}$$

S_e and S_p metrics are the ratio of well classified vessel and non vessel pixels, respectively. P_{pv} is the ratio of pixels classified as vessel pixel that are correctly classified. N_{pv} is the ratio of pixels classified as back ground pixel that are correctly classified. Finally, A_{cc} is a global measure providing the ratio of total well classified pixels.

Proposed Method Evaluation

Table 2: Performance Results on Drive Database Images Values

Image	S_e	S_p	P_{pv}	N_{pv}	A_{cc}
1	0.0721	0.9986	0.8236	0.9232	0.9225
2	0.6740	0.9909	0.8789	0.9688	0.9626
3	0.7362	0.9429	0.5462	0.9745	0.9252
4	0.6091	0.9939	0.8876	0.9698	0.9657
5	0.7126	0.9782	0.7108	0.9784	0.9596
6	0.7718	0.9722	0.6608	0.9838	0.9591
7	0.4853	0.9950	0.8783	0.9627	0.9595
8	0.7847	0.9573	0.5014	0.9878	0.9843
9	0.6516	0.9842	0.7170	0.9787	0.9649
10	0.7586	0.9694	0.6342	0.9829	0.9557
11	0.5935	0.9948	0.9062	0.9664	0.9633
12	0.7057	0.9544	0.5520	0.9760	0.9361
13	0.5486	0.9828	0.7100	0.9660	0.9520
14	0.0039	0.9999	0.8269	0.9226	0.9225

Table 2: Contd.,

15	0.0010	1.0000	0.8667	0.9109	0.9109
16	0.6523	0.9927	0.8781	0.9726	0.9673
17	0.7653	0.9624	0.5789	0.9838	0.9500
18	0.7611	0.9693	0.6418	0.9825	0.9553
19	0.1445	0.9999	0.5000	0.9238	0.9238
20	0.8012	0.9554	0.5092	0.9881	0.9470
Average	**0.5616**	**0.9797**	**0.7104**	**0.9651**	**0.9494**

Table 3: Performance Results on Drive Database Images Values with Statistics-Based Features

Image	Mn	St	Vr	Skw	Kut
1	0.0072	0.0845	0.0071	327.3697	3361.61
2	0.0684	0.2525	0.0637	277.3261	81.7521
3	0.1151	0.3192	0.1019	54.6490	487.6261
4	0.0503	0.2186	0.0478	574.6445	62.4821
5	0.0701	0.2553	0.0652	202.0194	58.2661
6	0.0766	0.2660	0.0707	144.7247	38.2850
7	0.0385	0.1923	0.0370	24.5565	173.7313
8	0.0812	0.2732	0.0746	95.5640	23.9540
9	0.0527	0.2235	0.0500	394.5850	150.7379
10	0.0781	0.2683	0.0720	135.8773	35.2782
11	0.0513	0.2207	0.0487	578.0996	61.5921
12	0.0943	0.2922	0.0854	86.7333	934.4851
13	0.0550	0.2279	0.0519	427.3822	156.6310
14	0.0671	0.0191	0.0671	12775.32	699813.0
15	0.0193	0.0103	0.0193	165956.2	8566631.0
16	0.0554	0.2287	0.0523	438.2400	159.4450
17	0.0835	0.2767	0.0766	107.1706	26.0870
18	0.0799	0.2711	0.0735	130.8889	33.2295
19	0.0220	0.0110	0.0220	96394.42	4373992.0
20	0.0859	0.2802	0.0785	84.8921	20.1658
Average	**1.2519**	**0.2070**	**0.0539**	**13960.53**	**253983.5**

Table 4: Performance Results on Drive Database Images Values with Other Statistics-Based Features

Image	Contrast	Correlation	Energy	Homogeneity
1	0.1848	0.7208	0.9827	0.9967
2	1.5955	0.7432	0.8417	0.9715
3	3.5591	0.6440	0.7286	0.9364
4	1.2013	0.7438	0.8804	0.9785
5	2.0369	0.6740	0.8327	0.9636
6	2.3437	0.6624	0.8128	0.9581
7	0.9979	0.7221	0.9068	0.9822
8	2.7361	0.6195	0.8005	0.9511
9	1.6171	0.6702	0.8680	0.9711
10	2.4665	0.6466	0.8098	0.9560
11	1.2393	0.7407	0.8778	0.9779
12	3.2521	0.6120	0.7670	0.9419
13	1.6437	0.6740	0.8647	0.9706
14	0.0132	0.6309	0.9990	0.9998
15	0.0055	0.4666	0.9997	0.9999
16	1.4024	0.7267	0.8675	0.9750
17	2.6153	0.6519	0.7962	0.9533
18	2.2830	0.6836	0.8083	0.9592
19	0.0069	0.4117	0.9996	0.9999
20	2.6917	0.6507	0.7908	0.9519
Average	**1.6946**	**0.6547**	**0.8617**	**0.9697**

CONCLUSIONS

Previous methods for blood vessel detection in retinal images can be classified into rule-based and supervised methods. This study proposes a method within the latter category. This method is based on a NN scheme for pixel classification, being the feature vector representing each pixel composed of gray-level and moment invariants based features. To the best of my knowledge, although moment invariants have been widely used over the years as features for pattern recognition in many areas of image analysis. The accuracy improves up to **0.9452**to **0.9494** compare to previous methods for the 20 test images in DRIVE database. Finally this method adopts a 7-D feature vector composed by the five gray-level and two moment invariants based features.

When the results on the DRIVE database is analyzed, the approach proposed in this paper provides highest average accuracy. And also calculated the statistical based features like Mean, Standard deviation, Variance, Entropy, Contrast, Correlation, Energy, Homogeneity, Skewness parameters are calculated and analyzed.

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